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Third Heart Sound Detection Using Wavelet Transform–Simplicity Filter

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***Abstract*— Heart failure and heart valvar diseases are chronic heart disorders which are potentially diagnosed using heart sound characteristics. Heart sound components S1 and S2 exhibit significant characteristics for valvar dysfunction while pathological S3 sound is a prominent sign for heart failure in elderly people. In this paper, a new automatic detection method of the S3 heart sound is proposed. The method is build upon wavelet transform–simplicity filter which separates S1, S2 and S3 sounds from background noise enabling heart sound segmentation even in the presence of heart murmurs or noise sources. The algorithm uses physiologically inspired criteria to assess the presence of S3 heart sound components and to perform their segmentation. Heart sound samples recorded from children as well as from elderly patients with heart failure were used to test the method. The achieved sensitivity and specificity were 90.35% and 92.35%, respectively.**

***Keywords:* Heart sound, Wavelet transform, Simplicity, S3 sound.**

I. INTRODUCTION

Heart sound is a key signal to assess the mechanical functional state of the heart. Its capacity to measure the cardiac mechanical system's state is comparable to the electrocardiogram in assessing the cardiac electrical system. Heart sound directly relates to the variations in pressure during the heart cycles, to the operation of the heart valves as well as the elasticity of the heart tissues. The timings between its main components, its morphology as well as its spectral content can be applied to directly estimate relevant cardiac parameters [1][2]. One of particular interest is the third heart sound (S3) component. The origins of the third heart sound are still controversial. The most accepted theory is the ventricular theory, which suggests that it is originated by ventricular compliance related rapid deceleration of the early transmitral flow and the associated vibration of the entire cardiac-blood pool system. In spite of the uncertainty regarding its geneses, the S3 sound in patients over 40 has been long regarded as a sign of ventricular dysfunction [3][5]. In fact, S3 is highly correlated to decreased cardiac output, reduced ejection fraction and elevated end-diastolic pressures which are most common in Heart Failure. A published retrospective analysis of the studies of Left Ventricular Dysfunction treatment trial demonstrated that patients with a third heart sound were at significant increased risk for hospitalization as well as at increased risk due to pump failure [4]. The third heart sound has also considerable clinical value in discriminating among several types of heart valve disease. For instance, it is most commonly auscultated with mitral regurgitation.

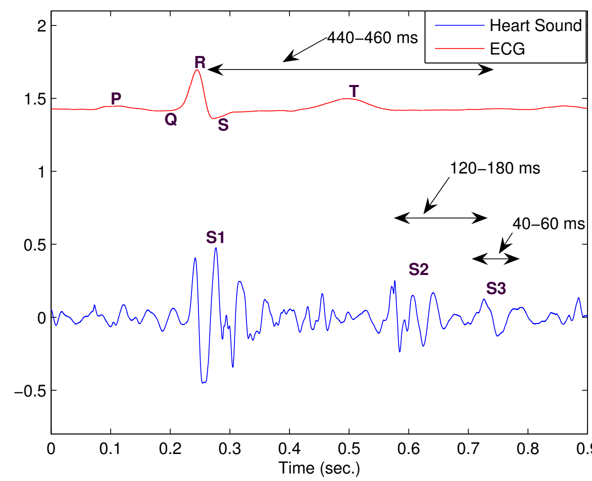

Fig. 1. ECG and Heart Sound showing a cycle containing components S1, S2 and S3.

The third heart sound is characterized by a low loudness, short duration and low frequency content (typically in the range 25-70Hz)[6]. These characteristics make it very difficult to hear using traditional auscultation devices. Its identification typically requires high proficiency level. Due to its clinical value as well as due to the required proficiency for S3 inspection, automated systems for S3 identification and characterization from phonocardiograms may be of high value to assist general clinicians as well as in designing systems for personal health applications in heart failure management.

Automatic identification of S3 from phonocardiograms is a relatively unexplored problem. In fact only few algorithms exist for S3 detection. These approaches may be broadly divided into methods that rely on the ECG as a synchronization signal and methods that explore the intrinsic characteristics of heart sound to identify the S3. In the former, the timing relationship between S3 and the R peak of the ECG may be explored. To avoid extra hardware requirements and clumsy wiring arrangement for ECG acquisition, several researchers have tried to identify S3 by several means of signal processing and statistics without using ECG as a reference. One of the recent works can be found in [7]. In [6][8] a matched wavelet approach has been suggested for S3 detection. In this approach, the impulse response of a 6th order Bessel bandpass filter is used due its resemblance to S3. This impulse response is adapted in the time and frequency domain in order to serve as the mother wavelet for matched wavelet decomposition. In [9] recurrence statistics are applied to derive a complexity measure in the 2D space. Image edge detectors are then applied in order to identify the boundaries of the S1 and S2 sound segments, which serve as a reference for S3 identification using the timing constraints presented in figure 1. The claimed results are highly promising. Unfortunately, the computational complexity and memory requirements of the algorithm are significantly high, hence limiting its practical usability in embedded systems and/or real time applications. In another algorithm the S-transform was applied to extract frequency contents of S3 sounds [10].

In this paper, we are proposing a novel method for S3 heart sound detection which exhibits low computational complexity and, hence, has the potential to be integrated into low power embedded systems. The heart sounds are first processed using a wavelet transform-simplicity (WT-S) filter in order to detect the main components of the heart sound, i.e. S1, S2 and S3, which are less complex. The proposed WT-S filter applies an adaptive thresholding procedure based upon a mean square error criterion in order to separate high complex background noise and heart murmurs (if any) from the less complex S1, S2 and S3 sounds. The S1 and S2 sounds are recognized by high frequency signatures. Finally, using the identified S2 sound lobes, several physiologically inspired criteria based on timings, loudness as well frequency content characteristics of S3 are applied to detect S3 presence as well as their delimitation.

The paper is structured as follows: in section II the important details of the proposed method are introduced; in section III some preliminary results presented and discussed, and finally, in section IV some main conclusions and future working directions are outlined.

II. Method

The proposed method is composed of 3 main stages: in the first stage, low frequency heart sound components S1, S2 and S3 are separated from high frequency murmur and background noise. In the second stage, S1 and S2 heart sounds are recognized. Finally in the last step, S3 heart sound is recognized based on previously detected S1 and S2 sounds (see figure 2). In the next subsection the applied simplicity measure is described. The main steps involved in the definition and implementation of the WT-S filter are outlined in subsection B. Finally, sections C and D present the detection strategy employed for S1/S2 and S3 detection, respectively.

Fig. 2. Block diagram of the involved stages in S3 sound detection.

A. Simplicity Measurement

Simplicity is computed by the eigen value spectrum method; being insensitive to additive noise, this technique is found superior over autoregressive and entropy for physiological signals [11]. Let $x(t)$ be the time series representing the heart sound signal, then a new delay vector is formed, $x_i(t) = [x(t), x(t-\tau), ..., x(t-(m-1)\tau))]^T$, where τ is delay and T is transpose. In the application of this method, two integer parameters (m, τ) are important to be suitably chosen. The application of an (m, τ) window to a time series of N data points results in a sequence of $P = N - (m-1)$ vectors. The delay vector $x_i \in R^m, i = 1, 2, ...P$, is constructed by shifting one sample time increment towards the right in the analysis window. These sequences construct an embedding matrix X,

$$X = \frac{1}{\sqrt{P}} \begin{pmatrix} x_1^T \\ x_2^T \\ . \\ . \\ x_P^T \end{pmatrix}, \quad (1)$$

On suitable selection of (m, τ), the embedding matrix provides information about complexity of the heart sound signal. This is measured by calculating the correlation matrix,

$$C = X^T X, \quad (2)$$

where X^T is the transpose of the embedding matrix X. Let D be diagonal matrix with the eigen values of C correlation matrix sorted in descending order, i.e. $D = diag\{\lambda_1, \lambda_2, ...\lambda_m\}$, where $\lambda_1 \geq \lambda_2 \geq .... \geq \lambda_m$. The diagonal matrix D is defined as singular spectrum of embedding matrix X. The dynamic changes are exhibited in the eigen value spectrum which can be measured by calculating the entropy of the eigen values. Let H be the entropy of the calculated normalized eigen values $\hat{\lambda}_k^i$. The entropy is defined by,

$$H(i) = \sum_{k=1}^{m} \hat{\lambda}_k^i log \hat{\lambda}_k^i, \quad (3)$$

If the base of the logarithm term is taken as 2, then another representation of complexity can be given as,

$$\Omega^i = 2^{H(i)}, \quad (4)$$

Here, the objective is to first emphasize the low complexity (high simplicity) of S1, S2 and S3 heart sound components. For the ease of application, simplicity is calculated for further processing by,

$$S^i = \frac{1}{\Omega^i}, \tag{5}$$

The values of parameters m, τ and N are experimentally chosen, and fixed to 10, T_s and 44, respectively.

B. Wavelet Transform - Simplicity Filter

The wavelet transform-fractal dimension based adaptive filter was developed for the enhancement and separation of lung sound (LS) and bowel sound (BS) from background noise [12]. Likewise, in solving the problem of S1 and S2 heart sounds separation from the murmurs, simplicity is derived using the aforementioned eigen value spectrum method of wavelet transformed heart sound signal which enhances the distinguishable peaks of S1, S2 and S3 sounds. It has already been mentioned that heart murmurs and background noise usually exhibit high frequency content which is more complex. Therefore, S1, S2 and S3 heart sound peaks can be peeled using an adaptive iteratively threshold.

The WT-S filter encompasses wavelet transform based on multiresolution decomposition to initially decompose heart sound into approximation and detail coefficients. The mother wavelet db6 is chosen from Daubechies wavelet family due to resemblance in shape to S1 and S2 sounds waveforms. Subsequently, simplicity (S) is computed from the decomposed signal, i.e. the approximation coefficients. The S peaks of S1, S2 and S3 are identified using an iteratively applied threshold, which is found based upon the mean square error. Furthermore, the suitable depth of wavelet decomposition level is also iteratively found using the mean square error criterion. The entire algorithm of decomposing heart sound followed by S peak threshold identification is described in the following few steps.

Step1: Heart sound is decomposed by wavelet transform using db6 as the mother wavelet. Let MRD^l be the l^{th} level decomposition, where $l = 1....L$, and L is the final depth level used in filtering.

Step2: Simplicity curve of decomposed signal is computed using the eigen value spectrum method described in the previous subsection (see in figure3(b)).

Step3: Peaks in simplicity curve of S1, S2 and S3 sounds are picked using the peak peeling algorithm (PPA) described in [13]. PPA algorithm finds not only peaks of S1, S2 and S3 sounds but also their durations. In many heart sounds samples, S3 sounds occur relatively nearer to S2 sounds as well as exhibit less simplicity. In these situations, peaks of S3 sounds in S curve are visible but its duration are not clearly segmented (see in figure 5). Subsequently, S2 sound duration become exceptionally high which is a clear sign of S3 sound presence in the heart sound. All peaks are extracted using PPA algorithm, in which, an adaptive threshold is computed by employing the mean square error criterion as the stopping criterion (see in figure 3(b)).

Step4: Two binary thresholds are constructed and applied to the thresholded simplicity curve ($SSTH^l$) achieved from the previous step (see figure 3(c)), first one is STh^l, which separates wavelet coefficients that are related to S1, S2 and S3 sounds, whereas second one, i.e. MTh^l, keeps wavelet coefficients related with murmur/background noise (see in figure 3(d, e)). These two binary threshold are,

$$STh^l = \begin{cases} 1 & SSTH^l \neq 0 \\ 0 & SSTH^l = 1 \end{cases}, \tag{6}$$

$$MTh^l = 1 - STh^l, \tag{7}$$

These thresholds are multiplied with the wavelet coefficients. The outcomes of these multiplications consist of the WT coefficients that are related to S1 and S2 sound waveform and the WT coefficients that are related to the presence of murmur.

Step5: The wavelet coefficients related to murmur/background noise are reconstructed in order to achieve suitable decomposition depth. Let Y_M^l be the multiresolution reconstructed signal with murmurs, then the stopping criterion is found using the mean square error given in equation (8).

$$STC^l = \mid E\{(Y_M^l)^2\} - E\{(Y_M^{l-1})^2\} \mid < \epsilon \tag{8}$$

where $E\{.\}$ represents expected value, and $\epsilon \in (0, 1)$, in this work it is fixed to 0.1. If equation (8) is not satisfied then the algorithm jumps to step1, and is repeated until the stopping criterion is found. The Y_M^1 is initialized with the expected value of the original heart sound signal.

C. S1 and S2 Recognition

After separating S1, S2 and S3 sounds from background noise/murmur, sounds are recognized based upon a high frequency marker that we have previously introduced in [14]. This marker is physiologically motivated by the accentuated pressure differences found across heart valves (both in native and prosthetic valves), leading to distinct high frequency signatures of the valve closing sounds. From the functionality of heart it is known that S2 sounds are produced with relatively high pressure. Hence, typically S2 sounds are recognized using high frequency marker. The high frequency marker can be achieved by computing Shannon energy of the detail coefficients in the wavelet decomposed heart sound signal (see in figure 5). Later, all heart cycles are found on the basis of detected S2 sounds (two contiguous S2 sounds construct a heart cycle). Since S1 sounds occur between two consecutive S2 sounds, hence, S1 sounds are recognized based on previously detected S2 sounds and systolic interval regularity.

D. S3 Heart Sound Detection

The method devised for S3 detection is composed by two main steps: (i) first the algorithms assesses if S3 components are present in the heart sound sample under analysis. (ii) Once S3 presence has been detected, the algorithm proceeds with to their actual identification using a set of physiologically inspired criteria. The following steps

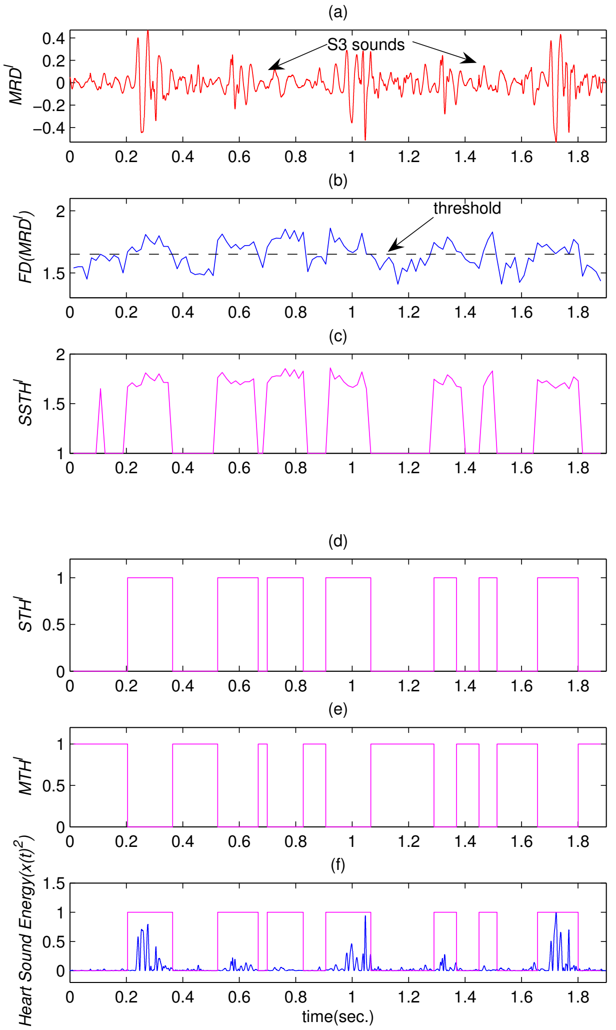

Fig. 3. WT-S filter in S3 identification. (a) Wavelet-decomposition at 5^{th} depth level, (b) Simplicity and iteratively chosen threshold, (c) Thresholded highly simplicity component, (d) Binary thresholded components related to S1, S2 and S3 sounds, (e) Binary thresholded background noise from highly simpler low frequency heart sound, (f) S1, S2 and S3 sounds are demarcated using *STh*.

summarize the procedure:

1) Availability of S3 Check: Two criteria have been considered to check for the availability of S3 sounds in a heart sound sample: (i) if the duration of more than 75% of the S2 sounds exceeds 250 ms, i.e., when WT-S filter is not able to separate boundaries of S2 and S3 sounds as is depicted in figure 4. (ii) If more than 75% small low complexity segments exhibiting low duration (50 ms–70 ms) are detected in the diastolic phase (see in figure 3(f)).

2) Recognition of S3 Sounds: S3 heart sounds are characterized by low loudness, small duration (typically between 40 and 60 ms), low frequency range (typically between 25 and 70Hz) and their diastolic nature, i.e. the S3 sound tend to originate around 150 ms after the onset of the A2 (aortic component of the S2 sound). Using these properties the

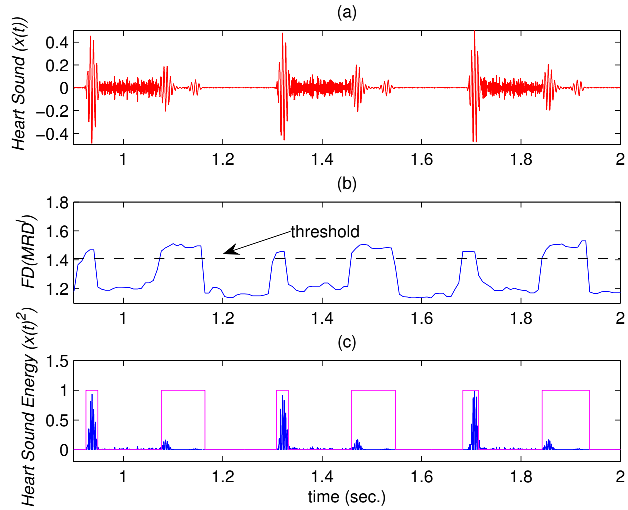

Fig. 4. An example of mitral regurgitation heart sound. (a) Wavelet-decomposition at 3^{rd} level depth, (b) Simplicity curve and iteratively chosen threshold, (c) S1, S2 and S3 sounds are demarcated using STh.

following validation criteria are defined in order to identify S3 sounds:

- Loudness of S3 sounds are usually very low compared to S1 or S2 sounds. Given a low complexity sound component, in order to be considered as a S3 sound it has to verify the inequality in equation 9.

$$(loudness)_{S3} < \frac{1}{3}(loudness)_{\{S1,S2\}} \tag{9}$$

- Due to falling between low frequency range (25–70 Hz), S3 heart sounds exhibit high simplicity. It is noteworthy that S3 sounds are found exhibiting more simplicity than S1 and S2 sounds, i.e. $S_{S3} > S_{\{S1,S2\}}$.
- The time interval between the onset of the S3 sound and the onset of the preceding S2 sound facilitates verifying S3 sounds. As it has already been mentioned this interval (t^{int}) has to verify (120 ms $< t^{int} <$180 ms).
- Finally, the duration criterion of the S3 sounds is verified using the aforementioned range, i.e. 40–60 ms.

III. Results and Discussion

Heart sound samples were collected in the Cardiology Section at the University Hospital of Coimbra from January 2007 to March 2007, under the guidance and instructions of an experienced cardiologist. Two heart sound samples were collected from http://www.egeneralmedical.com/listohearmur.html. The collected heart sound database includes sounds from children as well as heart sounds obtained from patients with heart failure. During acquisition, patients were asked to maintain silence and to make the least possible physical movements in order to maintain the integrity of the heart sound samples. Recording was performed with an electronic stethoscope from Meditron. The stethoscope has an excellent signal to

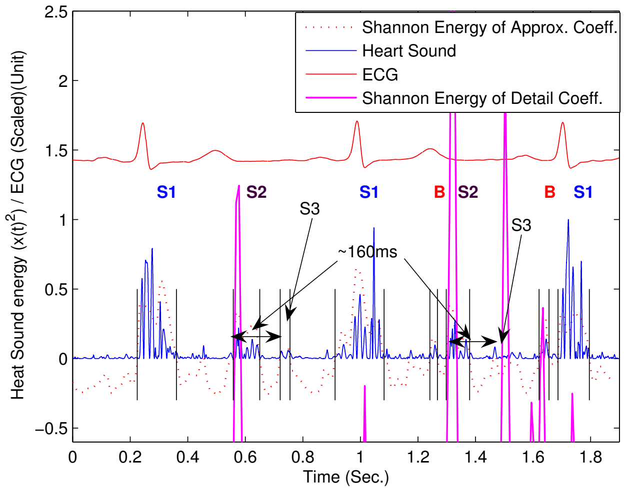

Fig. 5. S3 sounds occur after S2 sounds in the diastolic zone. Shannon energy of the Detail coefficients shows high frequency signature in S2 sounds. B is representing irrelevant heart sound segments.

noise ratio and extended frequency range (20 - 20,000 Hz). Although ECG is not considered in the present work, it was also recorded simultaneously to assess the segmentation efficiency of the algorithm. Heart sounds were digitized using a 16-bit ADC at 44.1kHz sampling rate. Sound samples were recorded for the maximum duration of one minute. All collected heart sounds were first preprocessed using a 4th order Butterworth high pass filter with cut-off frequency of 25 Hz in order to eliminate low frequencies produced by muscle and stethoscope movements.

TABLE I

SOME RESULTS OF S3 HEART SOUND IDENTIFICATION.

Patients	Detected	Not-detected	Wrong-detected
Heart Failure	60	5	3
Mitral Regurgitation	8	0	0
Children	35	6	5

The proposed method was tested with 5 heart sound samples. The prepared database includes heart sound samples of 2 children, 2 heart failure adult pateints and one patient with mitral regurgitation. Some achieved results regarding the number of detected S3 sounds are summarized in table1. The method has achieved a sensitivity of 90.35% and a specificity of 92.35% for the tested heart sounds. These values should be considered preliminary due to the reduced size of the database.

IV. CONCLUSIONS AND FUTURE WORKS

This paper introduces a new method for S3 heart sound detection using a wavelet transform-simplicity filter. The WT-S filter discriminates low frequency contained S1, S2 and S3 sounds from background noise/murmur. Thresholds for the separation for discrimination of S1, S2 and S3 sounds as well as the depth of wavelet decomposition are adaptively chosen using the mean square error as a stopping criterion. The S1 and S2 heart sounds are detected using high frequency signatures extracted from the separated S1, S2 and S3 sounds. The S3 sounds are then recognized using previously detected S2 sounds and a set of physiologically motivated criteria. The method exhibits adaptability for variety of population, which is one of the most prominent requirements for effective heart sound detection.

The prepared test database is too small to extract final conclusions on the method's performance. Nevertheless, the already achieved results are very promising.

V. ACKNOWLEDGMENTS

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